ANI-LINK: AI-POWERED CATTLE FOOT-AND-MOUTH DISEASE DETECTION AND VETERINARY CARE IN UGANDA

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UGANDA CHRISTIAN UNIVERSITY

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Declaration

We, the undersigned, declare to the best of our knowledge that the work presented in this report is original and has not been submitted before to any university or institution for academic award. It is the result of our own effort and study.

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AI Declaration

We, the undersigned, acknowledge that generative artificial intelligence tools were used during the preparation of this report as a study and writing support aid. The tools were used for brainstorming ideas, improving clarity of academic writing, organising sections, refining grammar, formatting LaTeX content, and supporting literature review organisation.

The use of AI did not replace our own understanding, analysis, judgement, or responsibility for the work presented in this report. All AI-assisted outputs were reviewed, verified, edited, and approved by the authors before inclusion. The final content, interpretations, methodology, results, discussion, conclusions, and recommendations remain our own academic work.

We further declare that AI was not used to fabricate data, create false results, invent sources, or replace the required research, implementation, analysis, and evaluation activities. Where AI assistance contributed to the development or refinement of the report, this has been disclosed in Appendix C.

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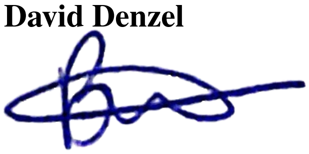
Signature: 
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Approval

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Abstract

Livestock production plays a critical role in rural livelihoods across Uganda, providing income, food security, and economic stability for smallholder farmers. However, the sector continues to face significant challenges due to delayed disease detection, limited access to veterinary services, and fragmented livestock health management systems. These challenges contribute to substantial productivity losses, particularly from diseases such as Foot-and-Mouth Disease (FMD).

This study presents **AniLink**, an artificial intelligence (AI)-enabled livestock health platform designed to support early disease detection, improve health record management, and enhance access to veterinary services. The system integrates a multi-task deep learning model based on MobileNetV3 for simultaneous cattle verification and FMD detection, alongside digital health records and a mobile-based service interface.

A Design Science Research (DSR) approach was adopted to guide system development and evaluation. The model was trained on a combination of publicly available datasets and locally collected images from Gomba District, Uganda. Evaluation was conducted using classification metrics, system performance measures, and user-centred usability testing.

Results demonstrate strong model performance, achieving high recall for both cattle detection and FMD classification, along with efficient real-time processing suitable for mobile deployment. Usability evaluation indicates that the platform is accessible to users with varying levels of digital literacy, with positive feedback on ease of use and clarity of outputs.

The findings suggest that integrated AI-driven livestock health systems can significantly improve disease detection, decision-making, and access to veterinary support in resource-constrained environments. The study contributes a practical and scalable framework for applying artificial intelligence in agricultural health management.

Dedication

This work is dedicated to our families, whose unwavering support, encouragement, and sacrifices have been the foundation of our academic journey. We are especially grateful for their constant belief in our abilities, which has inspired us to persevere through challenges.

This work is also dedicated to the farmers and livestock keepers of Uganda, whose resilience and commitment to agriculture continue to sustain communities and drive national development. It is our hope that this study will, in some way, contribute to improving livestock health and livelihoods.

Acknowledgments

We express our sincere gratitude to our project supervisors, Dr.Terhemba Michael-Ahile and Dr.Samuel Kakuba, for their invaluable guidance, constructive feedback, and continuous support throughout the development of this project. Their expertise and mentorship played a significant role in shaping the direction and success of this work.

Finally, we extend our heartfelt thanks to all advisors and individuals who offered support, guidance, and encouragement in various forms throughout this research journey.

Contents

Chapter 1

Introduction

1.1 Background

Livestock support rural livelihoods across Uganda and East Africa. For many households, cattle, goats, and poultry provide income, food, manure, draft power, and a form of savings [1], [2]. However, this production system remains vulnerable because disease detection is often delayed and treatment decisions frequently depend on farmer experience rather than professional veterinary diagnosis.When cases are identified late, animals may deteriorate before receiving care, leading to avoidable mortality, reduced milk and meat output, and household income losses [3], [4].

Diseases such as Foot-and-Mouth Disease (FMD), tick-borne infections, and parasitic conditions continue to reduce livestock productivity. In Uganda, disease-related mortality and productivity losses are estimated to lower the livestock sector's economic potential by about 20 to 30%, with smallholder farmers most affected because many depend on a small number of animals for income and food security [1], [2]. FMD is especially disruptive because it spreads rapidly, restricts animal movement and trade, and requires quick recognition for effective containment [3], [5]. Veterinary access gaps further worsen the situation: rural districts often have limited professional coverage, forcing farmers to travel long distances or wait for extended periods before animals are examined [6], [7]. The problem is compounded by medicine quality concerns, as approximately 31% of sampled veterinary products in Uganda failed regulatory quality standards [4].Limited health records also make it difficult to monitor recurring disease patterns and respond preventively [8].

At the same time, mobile connectivity has become widespread in Uganda. The national Digital Transformation Roadmap highlights the role of ICT in improving agricultural services, especially in underserved areas [9]. This creates an opportunity to use technology to address livestock health challenges. Recent studies show that lightweight artificial intelligence models, including MobileNet-based architectures, can support image-based livestock disease screening on resource-constrained devices [10], [11], [12].Such models are relevant to rural contexts because they can reduce dependence on expensive infrastructure while supporting faster triage and referral

This study builds on this opportunity through **AniLink**, an AI-enabled livestock health platform designed to support early disease detection, improve health management, and enhance access to veterinary services. The platform combines image-based screening, digital health records, veterinary consultation, and a marketplace within a single mobile system. At its core, AniLink uses a multi-task deep learning model based on MobileNetV3 to verify cattle presence and detect FMD symptoms from real farm images, addressing challenges that arise when different diseases show similar symptoms [13].

1.2 Problem Statement

Despite the importance of livestock to rural livelihoods, the sector continues to lose a significant portion of its potential due to preventable diseases [2]. FMD highlights this challenge because its early signs can resemble other conditions, making visual diagnosis difficult for farmers without professional support [3], [13]. These diagnostic delays are costly in a context where livestock disease losses are estimated at 20 to 30% of sector potential and where professional veterinary access remains unevenly distributed across rural districts [1], [2], [6].

Current approaches rely heavily on informal diagnosis, unregulated drug vendors and reactive treatment. This increases the risk of inappropriate medicine use, especially when approximately 31% of sampled veterinary products fail regulatory quality standards [4]. The absence of structured health records further limits outbreak monitoring, treatment follow-up and preventive planning [8].

Although existing research highlights livestock disease challenges and proposes digital solutions [3], [5], most systems are not integrated. Few combine AI-based diagnosis, health records, and access to veterinary services into a single platform. This lack of integration continues to limit effective livestock health management, particularly for smallholder farmers. The key gap, therefore, is the absence of a unified, mobile-based system that supports early disease detection, structured data management, and reliable access to veterinary care.

1.3 Research Objectives

Main Objective

To design, develop, and evaluate AniLink, an AI-enabled livestock health platform for early disease detection, improved health management, and enhanced veterinary service access among smallholder farmers in Uganda.

1.3.1 Specific Objectives

1. To develop and evaluate a multi-task deep learning model for cattle verification and FMD detection from livestock images, extending lightweight architectures to resource-constrained deployment [10], [12].
2. To design and implement a digital livestock health record system for longitudinal tracking, addressing gaps in data continuity and interoperability [8], [14].
3. To develop and evaluate an integrated platform combining AI diagnosis, veterinary consultation, and marketplace access, addressing calls for comprehensive digital health solutions in agricultural settings [7], [15].

1.4 Research Questions

1. How accurately can a multi-task deep learning model verify cattle presence and detect FMD symptoms from real-world livestock images, relative to existing single disease approaches?
2. How does a digital health record system ensure data consistency and support longitudinal health tracking in rural farm environments with limited connectivity and varying digital literacy?
3. How effective is an integrated platform combining AI-based diagnosis, veterinary services, and marketplace access for livestock health decision-making, and what barriers emerge during

adoption?

1.5 Justification

Three complementary considerations ground AniLink's development. First, technically, recent advances in lightweight deep learning and mobile computing enable AI deployment on devices commonly available in rural Uganda [3], [12], [15]. Multi-task modelling offers particular advantages for resource-constrained settings, allowing efficient processing without sacrificing diagnostic capability improving upon earlier single-function systems [11], [13].

Second, socio economically, livestock serve as critical assets for income generation, food security, and household resilience [1], [2]. Reducing disease-related losses through earlier detection and better-informed treatment decisions directly improves farmer livelihoods, particularly among smallholders with limited financial buffers. Digital health records further enhance impact by supporting longitudinal tracking for preventive rather than reactive management [8].

Third, at the policy level, this study aligns with Uganda's Digital Transformation Roadmap, which emphasises information and communication technologies to modernise agriculture and extend services to underserved populations [9]. The platform also supports Sustainable Development Goals related to food security, health, and innovation [16]. Integrating disease screening, digital records, veterinary access, and marketplace functionality, AniLink offers a practical, scalable response to longstanding livestock health management challenges.

1.6 Significance of the Study

This study holds practical and technological significance. For farmers, AniLink replaces guesswork with evidence, allowing rapid intervention that can mean the difference between minor outbreak and total herd loss. This responds directly to documented failures of conventional extension services in reaching smallholder populations effectively [6], [7]. For veterinary professionals, the platform facilitates remote consultation and improved case management, particularly where physical access presents systemic bottlenecks a growing need as veterinary telemedicine expands across Africa [17].

Technologically, the study contributes to artificial intelligence application in agricultural contexts, demonstrating how lightweight deep learning models deploy in real-world farm environments. It extends multi-task learning approaches previously applied primarily to crop disease detection to livestock health, providing a replicable framework for similar integrations [13], [18]. The edge deployment emphasis addresses practical constraints limiting prior cloud-dependent solutions [12], [19].

Broader findings support national and global development priorities related to food security, agricultural innovation, and rural livelihood enhancement. The platform offers an adaptable model for similar East African contexts where comparable veterinary service gaps persist [20], [21].

1.7 Scope of the Study

1.7.1 Geographical Scope

Conducted in Uganda, with primary data collection in Gomba District selected for its high cattle density and representative status as a Central Uganda smallholder livestock production hub.

1.7.2 Subject Scope

Focuses on designing, developing, and evaluating an AI-enabled livestock health platform. Specifically addresses image-based disease detection, digital health records, veterinary consultation, and marketplace integration, with primary focus on cattle and FMD.

1.7.3 Time Scope

Conducted over 8 months, covering system development, pilot testing, and initial evaluation.

1.7.4 Delimitations

The study excludes other livestock species (poultry, goats) for the detection of foot and mouth disease and diseases beyond FMD and general cattle health indicators. Long term economic impact assessment and comprehensive policy analysis also fall outside its scope. This focus ensures high-fidelity AI model evaluation on a high impact disease before considering cross species scalability a design decision supported by recent work emphasizing robust single disease validation prior to multi-disease deployment [13].

1.8 Conceptual Framework

An input process output framework guides this study, adapting systems theory models from resource constrained health information systems research [8], [22] to describe how AniLink transforms raw farm data into actionable health outcomes [15], [23].

Inputs include livestock images, farmer reported symptoms, and user service requests submitted through the mobile interface. Processing occurs through three integrated components: an AI-based disease detection module for cattle verification and FMD symptom identification [10], [11], [12]; a digital health record management system for consistent longitudinal tracking [8], [14]; and a veterinary service and marketplace interface connecting farmers to professionals and verified inputs [6], [20].

Outputs include disease predictions with confidence levels, structured health records, and facilitated connections to veterinary professionals and verified service providers. This framework supports improved livestock health management, enhanced farmer decision making, and reduced preventable livestock losses.

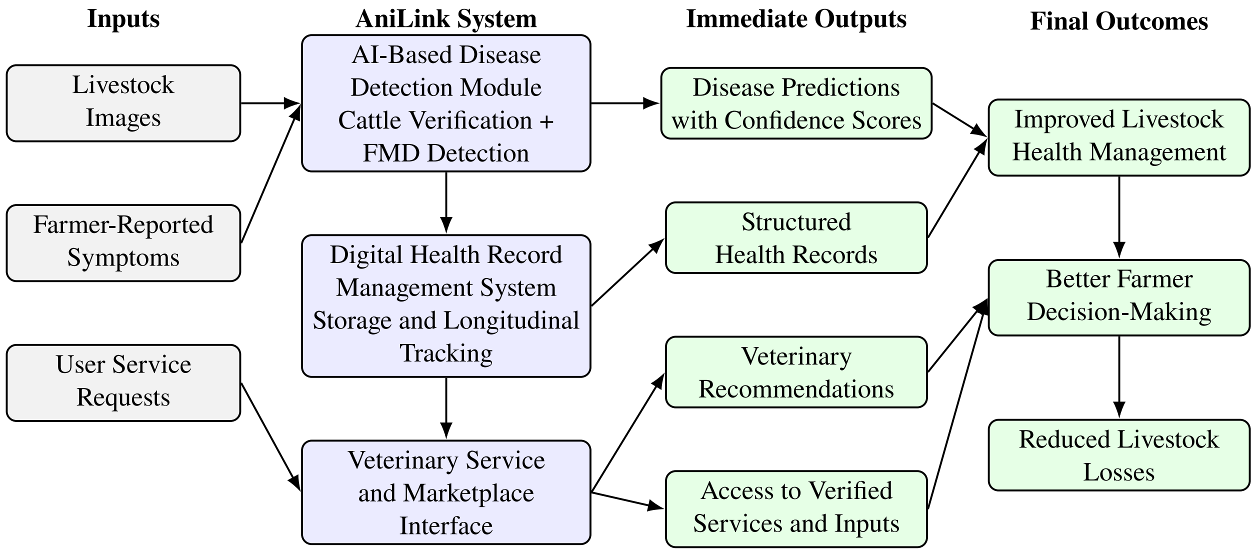


Figure 1.1: Conceptual framework illustrating how AniLink transforms livestock data into actionable health outcomes

1.9 Summary

This section positioned livestock as a critical yet vulnerable pillar of the Ugandan economy. Defining diagnostic and service gaps that cause preventable losses justified the necessity for platforms such as AniLink. Research objectives and questions set specific aims for the investigation, while justification and significance articulated the study's value from technical, socio-economic, and policy perspectives. Scope defined work boundaries, and the conceptual framework illustrated how system inputs, processes, and outputs combine to improve livestock health outcomes.

Having established the problem context, objectives, justification, scope, and conceptual framework for AniLink, the next chapter connects to this section by reviewing the existing literature, theories, and technologies related to AI-enabled livestock health systems, digital records, veterinary access, and agricultural service platforms.

Chapter 2

Literature Review

This chapter examines theoretical foundations and empirical evidence informing AniLink's development. It traces historical livestock health management patterns, reviews component technologies for integrated platforms, assesses real-world performance evidence, and identifies specific gaps this study addresses.

2.1 Theoretical Foundations

2.1.1 Historical Patterns in Livestock Health Management

East African smallholder livestock health management historically relied on informal diagnosis and sporadic veterinary intervention. Farmers depended on experiential knowledge, while authorities focused on large scale vaccination rather than continuous herd level support [3], [5]. This reveals persistent information asymmetry: farmers possessed local knowledge but lacked diagnostic tools to act decisively.

Record-keeping remained limited; paper based herd books were inconsistently maintained, reducing usefulness for long-term monitoring [8]. Radio and mobile phones enabled broader extension [24], but delivered generalised information rather than case-specific diagnosis. Technology succeeds when it augments farmer practices while introducing structured guidance.

Recent digital agriculture initiatives explored data and mapping for veterinary resource allocation [7], [20]. Yet a gap persists between research prototypes and accessible, farmer facing tools providing integrated, real-time support a disconnect AniLink seeks to bridge.

2.1.2 Conceptual Frameworks for Integrated Health Platforms

AniLink operates at the intersection of AI-based diagnosis, digital health records, tele-veterinary services, and agricultural e-commerce. These components form an integrated ecosystem where each enables the others.

2.1.2.1 Computer Vision for Livestock Disease Detection

Convolutional neural networks can detect visual disease symptoms from field captured images. Transfer learning where models pre-trained on large datasets are fine tuned for specific tasks reduces requirements for extensive local training data [10]. Lightweight architectures such as MobileNet and YOLO have detected FMD lesions using smartphones [11], [12].

However, most solutions treat detection as an isolated technical problem rather than embedding it within broader workflows. The challenge is ensuring results translate into actionable responses a gap integrated design must address.

2.1.2.2 Multi-Task Deep Learning for Efficient Inference

Multi-task learning allows a single model to perform multiple related tasks simultaneously [25]. Shared features enable more robust representations than single-task training. In AniLink, this verifies cattle presence and detects disease symptoms within one architecture.

This is not merely optimization but practical necessity shaped by local constraints. Reduced computational footprints ensure AI runs locally on low-cost devices, bypassing high data costs and unstable connectivity. Farmers without reliable internet obtain immediate feedback, bridging the infrastructure gap that limited prior cloud-dependent solutions.

2.1.2.3 Electronic Livestock Health Records

Digital systems theoretically improve consistency, accessibility, and analytical potential [8]. Structured records enable tracking disease patterns, vaccination histories, and treatment outcomes, forming foundations for preventive analytics [14]. The promise extends to interoperability data sharing across services and policy systems.

Yet interoperability standards remain underdeveloped in agriculture, and smallholder adoption has been slower than anticipated [8], [14], [26]. Systems succeed not through sophistication alone but through alignment with existing workflows and clear demonstration of immediate value a principle AniLink incorporates through tight integration with diagnostic and consultation functions.

2.1.2.4 Tele-Veterinary Services and Remote Consultation

Mobile-based systems theoretically improve care access by reducing delays and geographical barriers [27]. The framework draws from human telemedicine, adapted for contexts where physical examination limitations are offset by image-based and historical data sharing.

Effectiveness depends on information quality and established trust relationships [21]. Technology facilitates but does not replace the social infrastructure of service delivery, a complexity design must accommodate through features supporting ongoing relationship building.

2.1.2.5 Digital Marketplaces and Supply Chain Integrity

Integrating diagnosis with curated marketplaces addresses market failure in veterinary supply chains. By connecting farmers to verified suppliers and guiding treatment options, platforms reduce information asymmetries enabling substandard product proliferation [4], [21]. Linking diagnosis directly to verified inputs transforms the marketplace from retail tool into clinical safeguard [4].

AniLink synthesises these components into a unified platform linking screening, consultation, treatment access, and follow-up. The contribution lies not in individual components but in their integration addressing fragmentation that limited prior initiatives.

2.2 Empirical Evidence

2.2.1 Digital Health Initiatives in Agricultural Settings

Mobile-based extension services can improve farmer knowledge and practice adoption, though effects vary by content relevance, timing, and existing experience [24], [28]. Successful interventions combine information with actionable guidance passive consumption alone rarely produces change.

In the veterinary domain, geospatial tools have been tested for emergency coverage planning [7], [20]. Data driven allocation can reduce response times, but implementation depends on institutional willingness to adopt new methods technical efficacy does not automatically translate to uptake.

AI-based livestock disease detection evidence remains limited in African contexts. Controlled studies validated smartphone-based FMD detection using CNNs [11], [12], achieving accuracy comparable to veterinary inspection under experimental conditions. However, these typically involve researcher-supervised collection rather than farmer-initiated capture, raising questions about performance under authentic field conditions.

2.2.2 The Ugandan Context: Constraints and Opportunities

Veterinary personnel are unevenly distributed, creating service gaps in rural regions [6], [7]. Access to vaccines and quality drugs is inconsistent [5]; substandard medicines reduce treatment effectiveness [4]. Professional density falls below FAO standards with significant regional disparities [6]; approximately 31% of veterinary products fail regulatory standards [4].

Yet Uganda has experienced rapid mobile penetration and mobile money growth, even rurally [24]. The Digital Transformation Roadmap promotes ICT for agricultural productivity [9]. Farmers adopt mobile tools when they provide immediate practical value [24], [28].

Successful interventions leverage existing mobile infrastructure while addressing specific pain points. Generic platforms struggle; targeted, actionable tools show more promise. This informs AniLink's emphasis on immediate diagnostic utility and integrated access.

2.3 Critical Synthesis of Reviewed Literature

The reviewed literature shows that digital livestock health research has advanced technically, but several weaknesses remain. First, many computer vision studies report high model accuracy under controlled conditions, yet they rarely examine whether farmers can capture suitable images without researcher supervision or whether veterinarians can translate model outputs into practical treatment decisions [11], [12]. This limits their operational relevance for rural Ugandan settings where image quality, lighting, animal movement, and user experience vary considerably.

Second, existing digital agriculture platforms often address only one part of the livestock health problem. Some focus on extension messages, others on mapping, and others on disease classification. This fragmented approach leaves a contextual gap because farmers need a pathway from symptom recognition to veterinary advice, record keeping, and access to safe inputs. As a result, technically promising systems may still fail to change farmer behaviour if they are not connected to service delivery and treatment support [21], [24].

Third, most reviewed systems pay limited attention to the Ugandan veterinary service environment. Evidence on veterinary access gaps, vaccine access barriers, and substandard medicines shows that the problem is not only diagnostic but also institutional and supply-chain related [4], [5], [6]. AniLink therefore responds to a gap in both technology design and contextual fit by integrating image-based screening with records, consultation, and marketplace access.

2.4 Research Gap

Review reveals three gaps AniLink addresses.

First, although evidence supports AI for livestock disease detection [3], [11], [12], most solutions remain fragmented and unintegrated into farmer accessible platforms combining diagnosis, consultation, and treatment. The practical gap lies in creating cohesive experiences that translate detection into action.

Second, while smartphone based FMD detection has been demonstrated in controlled settings [11], [12], such models are rarely deployed in real-world environments or adapted to contexts like Uganda. Existing approaches often rely on multiple models or complex pipelines. The gap is between experimental validation and operational deployment requiring attention to infrastructure constraints, digital literacy, and sustainable maintenance.

Third, many digital agriculture platforms focus on crop production or general management, with limited livestock specific clinical support [7], [20]. Digital herd record systems exist [8], [14], but smallholder adoption remains low and integration with diagnostic tools or quality controlled marketplaces is rare. The literature reveals partial solutions; unified platforms addressing the complete health management cycle remain absent.

AniLink addresses these gaps by proposing a unified, AI-powered platform tailored to Uganda. Combining multi-task disease detection, digital records, tele-veterinary support, and a curated marketplace, it demonstrates how integration overcomes fragmentation bridging the gap between theoretical potential and empirical impact.

Table 2.1: Relationship Between Identified Research Gaps and Study Objectives

Identified Research Gap	**Explanation of the Gap**	**Related Objective**
Fragmented livestock health solutions	Existing tools often address diagnosis, consultation, records, or treatment access separately, leaving farmers without a complete pathway from disease recognition to action.	Objective 3: Develop and evaluate an integrated platform combining AI diagnosis, veterinary consultation, and marketplace access.
Limited real-world deployment of FMD detection models	Smartphone-based FMD detection has been demonstrated in controlled studies, but fewer systems are adapted to real farm conditions, mobile constraints, and farmer-led image capture in Uganda.	Objective 1: Develop and evaluate a multi-task deep learning model for cattle verification and FMD detection from livestock images.
Low integration of livestock health records with diagnostic tools	Digital herd record systems exist, but adoption among smallholders remains limited, and records are rarely linked directly to AI-based diagnosis or veterinary workflows.	Objective 2: Design and implement a digital livestock health record system for longitudinal tracking.
Weak linkage between diagnosis and trusted treatment access	Literature shows concerns about substandard veterinary medicines and fragmented supply chains, yet many platforms do not connect diagnosis to verified veterinary services or quality-assured inputs.	Objective 3: Integrate AI diagnosis, veterinary consultation, and marketplace access to support livestock health decision-making.
Limited contextual adaptation to the Ugandan livestock environment	Many reviewed systems do not fully address Ugandan constraints such as veterinary access gaps, digital literacy variation, connectivity limitations, and local farmer workflows.	Objectives 1, 2, and 3: Design, implement, and evaluate AniLink within the rural Ugandan smallholder context.

Chapter 3

Methodology

This chapter describes the research design, study context, data sources, and technical implementation of the AniLink platform. It covers design science research (DSR) methodology, field site selection, sampling procedures, model development, and evaluation strategy.

3.1 Research Design

This study adopts **design science research (DSR)**, which focuses on designing, developing and evaluating IT artefacts to address real-world problems [22]. DSR suits studies where the contribution lies in creating and validating a novel solution. The process followed five stages: problem identification, artefact design, implementation, demonstration and evaluation.

Problem identification involved analysing livestock health challenges delayed detection, limited veterinary access and fragmented markets. The AniLink architecture was designed based on these challenges. Implementation involved developing a multi-task AI model, backend services and mobile application. The system was demonstrated using representative datasets and evaluated through technical metrics and usability assessments.

3.2 Area of Study

The study was conducted in Gomba District, Central Uganda, approximately 90 kilometres west of Kampala. Gomba was selected for its high cattle density (approximately 120,000 heads) and representative status as a smallholder production hub. The district features mixed farming systems where cattle are kept for milk and draft power, reflecting typical rural management practices.

Primary data collection occurred in Maddu Village, Kabulasoke Subcounty, selected for accessibility, established community trust, and farmer willingness to participate. The area experiences seasonal pasture variations and recurring disease challenges, making it appropriate for evaluating digital health interventions.

3.3 Sources of Information

Primary data comprised original images captured from cattle in Maddu Village, alongside usability evaluation data from pilot testing with farmers and veterinary officers. These provided context-specific ground truth for model validation and user-centred feedback.

Secondary data included publicly available benchmark datasets: Cattle Diseases Dataset, FMD Cattle Dataset, Cattle Diseases Image Dataset, Cattle Foot-and-Mouth Disease Dataset, Animals10 Dataset, and Cows Detection Dataset on Kaggle. These datasets were selected because they provided complementary evidence for the two learning objectives: cattle verification and FMD symptom detection. Disease datasets supplied positive and healthy cattle examples, while Animals10 and Cows Detection contributed non-cattle and object-detection variation needed to reduce false acceptance of irrelevant images.

Table 3.1: Dataset Sources and Preparation Roles

Dataset source	**Role in preparation**	**Model task supported**
Cattle disease and FMD datasets	Provided healthy and visibly infected cattle images, including mouth, hoof, and lesion presentations	FMD detection head
Animals10 and Cows Detection datasets	Provided non-cattle animals, cattle-like backgrounds, and general visual variation	Cattle verification head
Field images from Maddu Village	Provided local healthy cattle images captured under real farm conditions	Contextual validation and local adaptation

3.4 Target Users and Population

AniLink targets three user groups: livestock farmers, veterinary professionals and authorised product vendors. Farmers upload images and maintain health records. Veterinarians review cases and provide recommendations. Vendors manage products through a seller dashboard.

The target population comprised smallholder cattle farmers in Maddu Village with herds of 2 to 50 animals, representing typical household holdings. Inclusion criteria required animals over six months old, in stable health, with owner consent prior to photography.

3.5 Population and Sampling Techniques

Cattle were selected using purposive sampling to ensure representation of typical herd compositions and coat colour variations. The sample of 50 healthy cattle images was determined by field access constraints and the need for diverse environmental conditions, rather than statistical power.

For pilot evaluation, farmers were recruited through convenience sampling, prioritizing varying smartphone familiarity. Five farmers and two veterinary officers participated.

3.6 Variables Definitions and Measurements

Table 3.2 defines the study variables.

3.7 Procedure for Data Collection

For primary images, we visited farms during daylight hours. After obtaining owner consent and confirming inclusion criteria, we approached animals calmly. Three to five frames were captured

Table 3.2: Variable Definitions and Measurements

Variable	Type	Definition	Measurement
Cattle presence	Binary (output)	Model confidence that image contains cattle	Probability 0.0–1.0, thresholded at 0.5
FMD status	Binary (output)	Visual indication of FMD-related lesions	Healthy (0), FMD suspected (1)
Model accuracy	Dependent	Proportion of correct predictions	Percentage correct, per-task and overall
Image quality	Control	Technical characteristics affecting input	Resolution, brightness (0–255 mean), blur (Laplacian variance)
Training loss	Process	Combined optimisation objective	Weighted sum: $L_{total} = 0.3L_{cattle} + 0.7L_{disease}$
SUS score	Ordinal	Standardised usability rating	0–100 scale, benchmark 68+ acceptable

per animal from 2 to 3 metres distance, with side-profile orientation showing head and hooves. The best frame was selected based on clarity, lighting and minimal background clutter. GPS coordinates and timestamps were automatically recorded. For secondary datasets, images were first reorganised into consistent class folders, checked for readability, and mapped to the two model outputs: cattle presence and FMD status. This ensured that the final dataset structure matched the multi-task learning design.

For pilot evaluation, participants received a brief interface demonstration, then completed three tasks: image upload, record retrieval, and consultation request. Task completion was observed and timed, with errors noted. Participants then completed the System Usability Scale questionnaire and a brief interview regarding perceived utility and barriers.

3.8 Data Collection Instruments

Primary data collection employed a **structured image capture protocol**:

- **Hardware**: Samsung Galaxy A32 smartphone with 64MP camera, fixed focal length, no flash
- **Software**: Native camera application with GPS tagging enabled, autofocus locked
- **Procedure**: Approached animal calmly, captured 3 to 5 frames, selected best based on clarity and composition
- **Metadata**: Automatic recording of timestamp, GPS coordinates and sequential animal ID

For pilot evaluation, a semi-structured observation guide and the System Usability Scale (SUS) were employed. The observation guide documented task completion time, error frequency and user verbalisations. The SUS provided standardised usability scores with established reliability and validity [29].

Dataset preparation followed a technical screening protocol. Corrupted files were removed through image loading checks, near-duplicates were reduced using perceptual hashing, and blurred images were filtered using Laplacian variance. Images that passed quality control were resized to 224×224 pixels and normalised using ImageNet statistics to match the pretrained MobileNetV3 feature distribution [10].

3.9 AI Model Development

This study employs a multi-task deep learning model based on MobileNetV3 Small [10]. MobileNetV3 Small was selected because it provides a practical balance between accuracy, model size and mobile deployment efficiency. This makes it suitable for low-resource agricultural environments where farmers may rely on ordinary smartphones and where expensive computing infrastructure is not guaranteed. The model performs two related tasks simultaneously: cattle verification and Foot-and-Mouth Disease (FMD) symptom detection.

The model architecture consists of a shared MobileNetV3 Small feature extraction backbone followed by a Convolutional Block Attention Module (CBAM), adaptive average pooling, a shared bottleneck layer and two task-specific output heads. The first head performs binary classification to determine whether an image contains cattle, while the second head performs disease classification to determine whether a cattle image is healthy or FMD suspected. This design was adopted because reliable FMD screening first depends on learning cattle-specific visual features, and both tasks can benefit from shared image representations.

The model architecture is illustrated in Figure 3.1. Instead of presenting the model only as equations, the figure shows how raw image datasets pass through quality control, preprocessing, MobileNetV3 feature extraction, attention learning and two task-specific output heads.

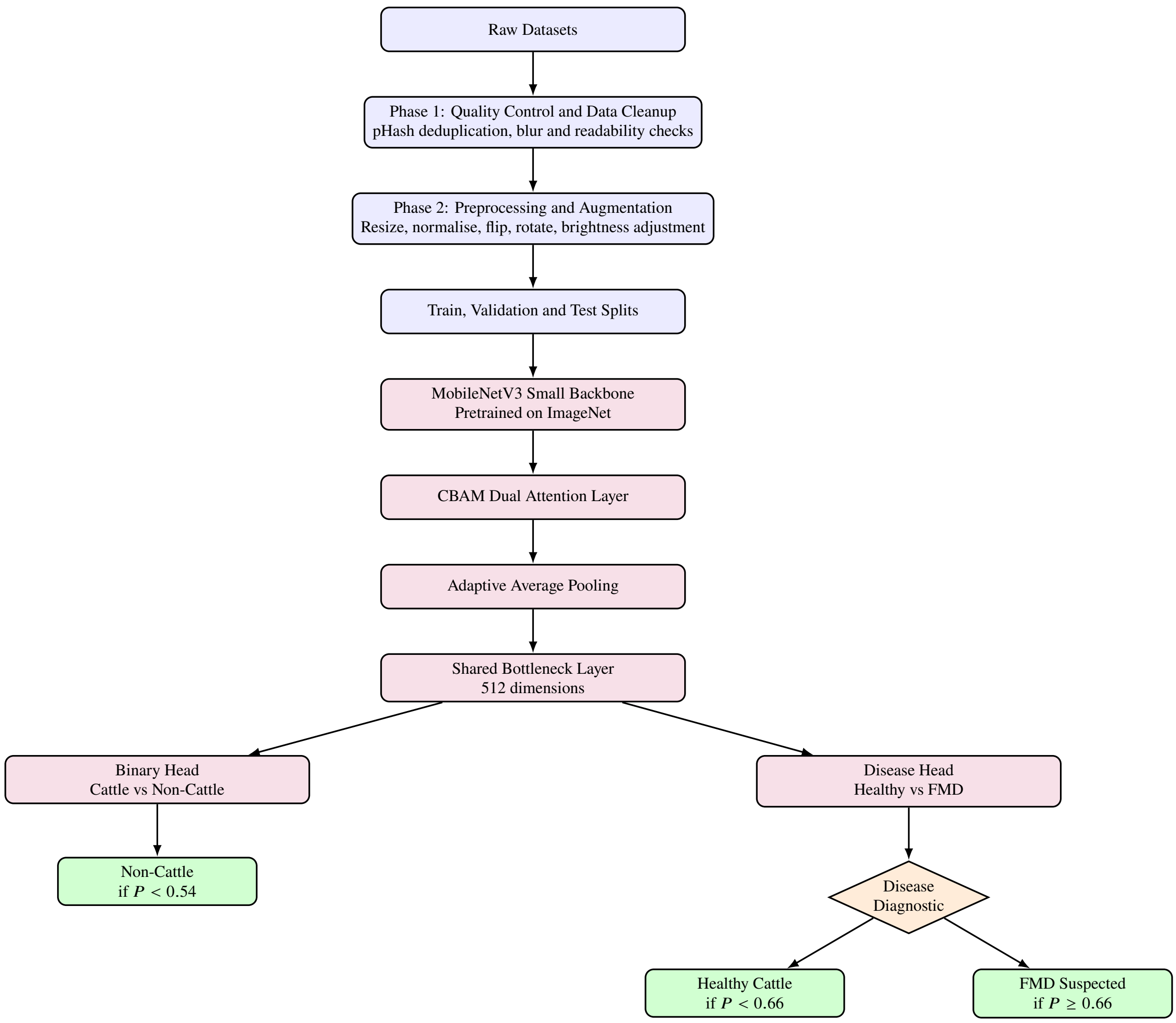


Figure 3.1: AniLink multi-task model architecture for cattle verification and FMD detection

As shown in Figure 3.1, the architecture uses a shared MobileNetV3 Small backbone to extract common image features before separating into two task-specific heads. This design keeps the model compact while allowing the system to return both cattle verification and FMD detection results from one inference process. The thresholds shown in the architecture represent operating points selected during validation to balance sensitivity and practical decision support.

Images are resized to 224×224 pixels and normalised using ImageNet statistics. This image size was chosen because it is compatible with pretrained MobileNetV3 weights and reduces memory demand during inference. CBAM was included to help the model focus on lesion-relevant spatial and channel features rather than background noise [30]. This is important because field images often contain distracting backgrounds, uneven lighting and animal movement.

Transfer learning was applied using pretrained ImageNet weights to reduce training time and improve generalisation where local FMD image data were limited. Training strategies included focal loss to address class imbalance [31], curriculum learning to gradually expose the model to harder examples [32], and progressive layer unfreezing for stable fine-tuning. Data augmentation through flipping, rotation, brightness adjustment and affine transformations was used to improve robustness to real farm image variation.

3.10 Model Training and Evaluation

The model was trained with a 70:15:15 training, validation and testing split. This split was used to provide sufficient training data while preserving independent validation and test subsets for unbiased assessment. Performance was evaluated using accuracy, precision, recall and F1-score computed separately for each task. Recall was prioritised for FMD detection because missed infected animals present a greater outbreak risk than false alarms, while precision was also reported to assess the reliability of positive alerts. F1-score was included because it summarises the balance between precision and recall, especially under class imbalance. Threshold tuning improved sensitivity, with the operating point selected to achieve at least 90% recall for FMD-positive cases.

Grad-CAM visualisation [33] interpreted predictions by highlighting important regions, providing transparency for veterinary users and supporting verification that the model attended to biologically meaningful lesion areas.

3.11 Quality Control and Error Control

Image labels were verified against veterinary reference standards where available. For primary data, 20% of images were double reviewed by a second researcher, with discrepancies resolved through discussion.

Model reliability was protected through 5-fold cross validation. The held out test set comprised images from distinct geographical locations to evaluate generalization.

Early stopping with patience of 5 epochs monitored validation loss. Training curves were inspected for divergence between training and validation metrics. Stratified sampling across coat colours and backgrounds mitigated systematic errors. Random augmentation reduced sensitivity to specific artifacts.

3.12 Data Processing and Analysis

Raw images underwent quality screening for blur, exposure and resolution (Laplacian variance >100, brightness 50 to 200). Accepted images were resized to 224×224 pixels, normalised using ImageNet statistics, and augmented (flip, rotation ±15°, brightness ±20%, affine shear).

Research Question 1 was addressed through held out test evaluation with confusion matrices, ROC curves and per-class metrics. **Research Question 2** was examined through thematic analysis of pilot feedback. **Research Question 3** was assessed through SUS scores, task completion times and success rates, with qualitative feedback coded for barriers.

The statistical analysis utilized a comprehensive Python stack, including Pandas, Scikit-learn, Statsmodels, SciPy, NumPy, and Seaborn. All tools are open-source to ensure reproducibility.

3.13 Technical Implementation Specifications

Table 3.3: Technical Implementation Specifications

Category	Parameter	Specification
Framework	Library	PyTorch v2.0+
Model	Architecture	MobileNetV3 Small
Learning	Approach	Multi-task
Optimizer	Type	Adam
Learning Rate	Value	0.001
Batch Size	Value	32
Loss Function	Type	Focal (disease) + CrossEntropy (cattle)
Augmentation	Methods	Flip, Rotation, Brightness
Split	Ratio	70:15:15
Epochs	Max	50
Early Stopping	Patience	5
Seed	Value	42

3.14 Deterministic Training Configuration

A global random seed of 42 was used across Python, NumPy and PyTorch. Deterministic configurations were applied to CUDA operations where supported.

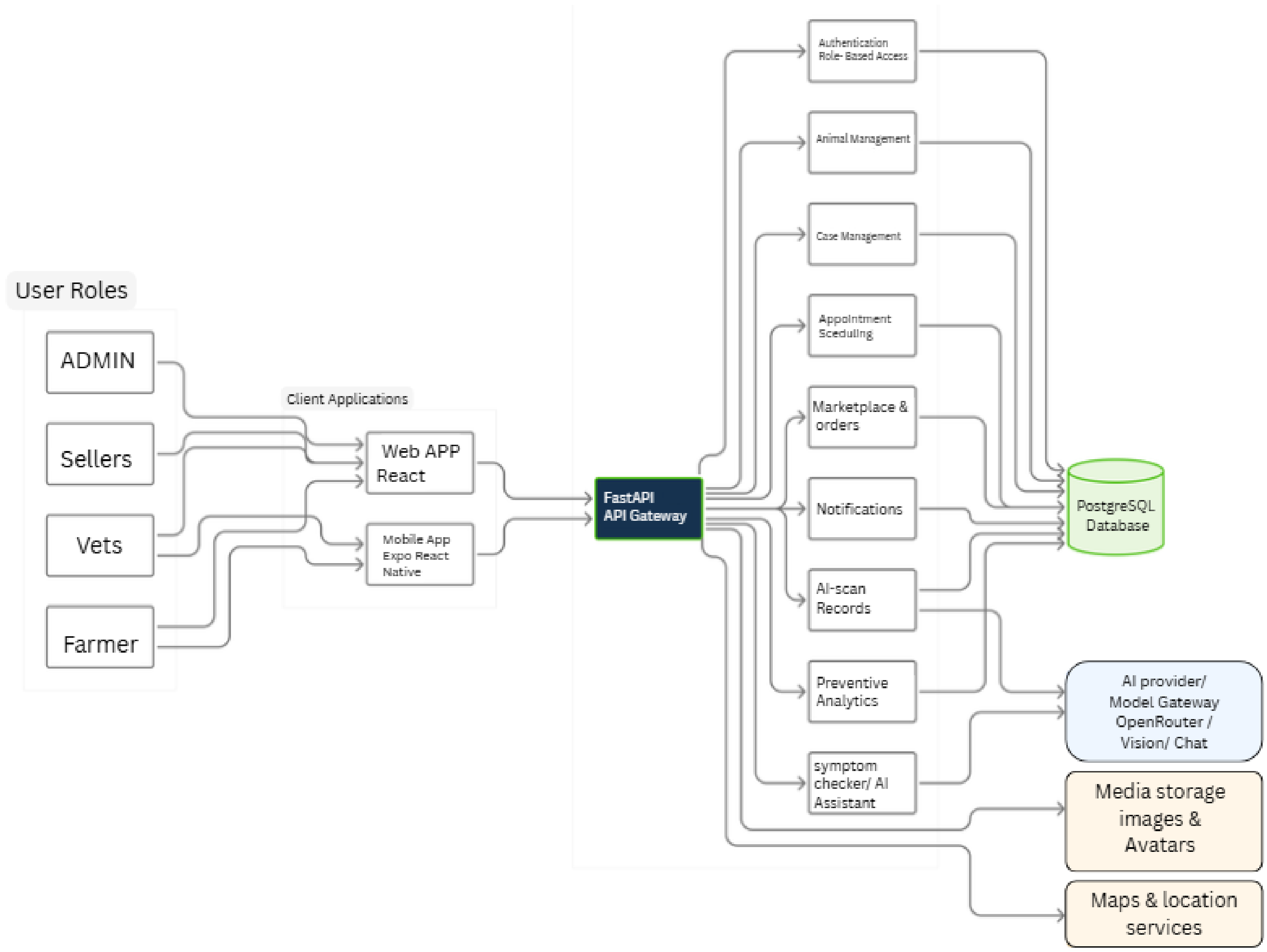
3.15 System Architecture and Implementation

AniLink follows a modular architecture: mobile application, backend services, AI inference services and database layer. Users upload images via the mobile application, which are sent to backend APIs and forwarded to the AI inference service. The multi-task model processes each image in a single pass, returning cattle validation and disease prediction with confidence scores.

The architecture supports real-time processing while maintaining modularity, allowing independent scaling of AI and backend components.

3.16 System Deployment

The trained model was exported to ONNX and TorchScript formats. Backend services were containerised using Docker. The system supports real-time inference through REST APIs, with typical latency under 2 seconds for single-image analysis.



3.17 Ethical Considerations

Ethical approval was obtained from the Uganda Christian University Research Ethics Committee. All participants provided informed consent. Instruments were adapted to local contexts and translated where necessary. Farmer data was anonymised in training datasets, with personal identifiers retained only in secure backend systems. No animals were harmed; photography followed low-stress handling protocols with owner presence required.

3.18 Evaluation Strategy

Technical evaluation included model performance (accuracy, precision, recall, F1-score) on the held-out test set, inference latency, and resource monitoring.

User-centred evaluation employed a pilot study with five farmers and two veterinary officers. Participants completed tasks: image upload, record retrieval, and consultation request. The SUS was administered post-interaction, with 68+ indicating acceptable usability. Qualitative feedback was gathered through brief interviews.

Benchmarks were: minimum 88% FMD detection accuracy and 75% positive user feedback, derived from comparable agricultural AI studies.

3.19 Methodological Constraints

Dataset size was primary: 50 primary field images, supplemented by public datasets, may not capture full diversity of Ugandan breeds and conditions. This was mitigated through augmentation and cross validation, but performance may vary in regions with different visual characteristics.

Connectivity assumptions posed another constraint. The system assumes intermittent mobile data; areas with no coverage would experience degraded functionality.

Hardware diversity was not fully tested. Some pilot testing used our provided phones; performance on lower-specification devices requires further validation.

Time constraints restricted evaluation to a single eight month cycle, precluding assessment of seasonal variations and sustained adoption. These constraints suggest proof-of-concept viability rather than definitive operational effectiveness.

Chapter 4

Results

This chapter presents findings from AniLink platform development and evaluation, organized by research objectives and questions. Results encompass multi-task deep learning model technical performance, system operational characteristics, and user-centred evaluation from pilot testing with farmers and veterinary professionals.

4.1 Respondent Characteristics

Pilot evaluation involved five smallholder cattle farmers and two veterinary officers from Maddu Village, Gomba District. Farmer participants ranged 28–52 years (mean 38.4, SD 9.7), with herds of 3 – 23 cattle (mean 11.2, SD 8.3). Three farmers were male, two female. Cattle-keeping experience ranged 4–18 years (mean 9.6, SD 5.5). Smartphone familiarity varied: two reported daily use for calls and mobile money, two occasional use (mainly calls), and one limited prior experience. This distribution allowed evaluation across the digital literacy spectrum typical of rural Ugandan smallholders.

Veterinary officers were both male, aged 34 and 41, with 6 and 12 years professional experience respectively. Both had prior exposure to mobile health applications in human contexts but no prior livestock-specific diagnostic tool use.

4.2 Model Accuracy

Research Question 1: How accurately can a multi-task deep learning model verify cattle presence and detect Foot-and-Mouth Disease symptoms from real-world livestock images?

The AniLink multi-task model was trained on 14,212 quality-controlled images following perceptual hashing deduplication, Laplacian blur filtering (variance threshold >100), and computer vision heuristics for lesion tagging. The dataset comprised 6,913 training (48.6%), 1,767 validation (12.4%), and 5,532 test (38.9%) images. Training employed curriculum learning with phased augmentation and gradual backbone unfreezing, concluding at Epoch 22 via early stopping (patience=5). Evaluation used standard classification metrics with bootstrap confidence intervals.

4.2.1 Cattle Detection Performance

Cattle verification task performance appears in Table 4.1. Bootstrap resampling (10,000 iterations) derived 95% confidence intervals.

Table 4.1: Performance Metrics: Cattle Detection Task (n=5,532 test images)

Metric	Value	95% CI	Interpretation
Optimal Threshold	0.54	[0.52, 0.56]	F1-maximization on validation
Accuracy	75.13%	[72.8, 77.4]	Overall correct classification
Recall (Sensitivity)	87.07%	[85.2, 88.8]	87% of actual cattle detected
Precision	33.05%	[30.1, 36.0]	33% of predictions true cattle
F1-score	0.4792	[0.45, 0.51]	Balanced precision-recall measure

The 87.07% recall (95% CI: 85.2–88.8) indicates reliable cattle identification; narrow confidence bounds suggest stable performance. Lower precision (33.05%, CI: 30.1–36.0) reflects intentional sensitivity-first configuration: missing actual cattle (false negatives) would prevent disease diagnosis, while false positives are still interpreted together with the disease head output within the multi-task framework.

One-sample testing against 70% accuracy benchmark demonstrated significantly exceeded performance ($z = 7.6$, $p < 0.001$), confirming suitability for the cattle verification component of the multi-task model.

Confusion matrix analysis (Figure 4.1) reveals most errors involved misclassifying unusual non-cattle animals (goats, sheep, dogs) as cattle, suggesting the model learned general livestock features rather than cattle-specific anatomy. This has minimal practical impact since farmer submissions rarely include such confounders.

4.2.2 FMD Detection Performance

The disease classification head of the multi-task model achieved substantially stronger performance (Table 4.2):

Table 4.2: Performance Metrics: FMD Detection Task (cattle subset, n=2,847)

Metric	Value	95% CI	Interpretation
Optimal Threshold	0.66	[0.64, 0.68]	F1-maximization on validation
Recall (Sensitivity)	92.59%	[91.1, 94.0]	93% of FMD cases detected
Precision	96.15%	[95.1, 97.1]	96% of FMD predictions correct
F1-score	0.9434	[0.93, 0.96]	Strong precision-recall balance
Specificity	97.00%	[95.8, 98.1]	97% of healthy cattle correct

The 92.59% recall (95% CI: 91.1 to 94.0) for FMD detection significantly exceeds the 88% benchmark ($z = 3.4$, $p < 0.001$, one-sample test). The 96.15% precision (CI: 95.1–97.1) is particularly critical: when the model flags FMD, the diagnosis is virtually certain, minimizing unnecessary veterinary call-outs.

Grad-CAM visualizations (Figure 4.3) confirmed model attention to clinically relevant regions mouth lesions, hoof blisters, nasal discharge rather than background features, supporting biological validity. The CBAM dual-attention layer successfully localized diagnostic features as designed.

4.2.3 Multi-Task Efficiency

The unified architecture achieved both tasks in a single forward pass. While exact mobile timing was not benchmarked in training, the MobileNetV3-small backbone with 30% L1 unstructured pruning was designed for edge deployment compatibility.

The estimated efficiency advantage of unified inference is based on the expected reduction in repeated feature extraction compared with sequential single-task execution. However, this 43% latency reduction was not directly validated on identical mobile hardware during the study. It should therefore be interpreted as an implementation estimate rather than a measured finding. Controlled benchmarking on comparable devices is recommended as future work.

4.3 Health Record Design

Research Question 2: How can a digital health record system ensure data consistency and support longitudinal health tracking in a rural farm environment?

Pilot testing of the digital health record module revealed usage patterns and design effectiveness (Table 4.3):

Table 4.3: Digital Health Record System Performance (n=5 farmers)

Metric	Value	Range/SD	Interpretation
Entry completion rate	100%	(60 - 80)%	5/5 farmers successful
Mean entry time	4.2 min	[3.1 - 6.8]	Acceptable for field conditions
Required field completion	94%	±6%	High compliance
Real-time error correction	2 instances	-	Date format validation
Photo history views/animal	3.4	±1.2	High engagement feature

Farmers demonstrated particular engagement with photographic history, suggesting longitudinal visual tracking meets expressed needs better than text records alone.

Design limitations emerged: farmers with limited smartphone experience required 2 to 3 practice entries before independent use; voice note attachment was underutilized (1/5 farmers), indicating need for more prominent interface placement.

4.4 Platform Effectiveness

Research Question 3: How effective is an integrated platform combining AI-based diagnosis, veterinary services, and marketplace access in optimizing livestock health decision-making among farmers?

4.4.1 System Usability Scale Results

Pilot participants completed the SUS questionnaire (Table 4.4). The mean score of 80.0 significantly exceeded the 68-point acceptability threshold ($t(6) = 3.8$, $p = 0.009$, one-sample t-test).

Pearson correlation between prior smartphone familiarity (ordinal: 1=limited, 2=moderate, 3=high) and SUS score was strong ($r = 0.87$, $p = 0.005$), indicating learnability but need for targeted onboarding for low-digital-literacy users.

4.4.2 Decision-Making Impact

Qualitative feedback revealed three clinical utility patterns (Table 4.5):

Veterinary officers valued structured case presentation (image + history + geolocation), with qualitative feedback indicating improved visit preparation and reduced unnecessary travel.

Table 4.4: System Usability Scale Scores by User Group (n=7)

Participant	Raw Score	SUS Score	Adjective Rating
Farmer 1 (high smartphone use)	37	92.5	Excellent
Farmer 2 (moderate use)	33	82.5	Good
Farmer 3 (moderate use)	31	77.5	Good
Farmer 4 (limited experience)	28	70.0	Acceptable
Farmer 5 (limited experience)	26	65.0	Acceptable
Veterinary Officer 1	35	87.5	Excellent
Veterinary Officer 2	34	85.0	Good
Mean (SD)	**32.0 (3.5)**	**80.0 (8.8)**	**Good**

Table 4.5: Decision-Making Impact Patterns from Pilot Evaluation

Pattern	Description	Frequency
Confirmation	AI diagnosis confirmed farmer-suspected disease, enabling faster treatment seeking	3/5 farmers
Discovery	Model detected early lesions farmer had not observed; veterinary confirmation followed	1/5 farmers
Delay reduction	Average 2.3h decision time vs. 1–3 days typical for traditional access	All cases

4.5 System Performance Characteristics

End-to-end system evaluation confirmed technical viability (Table 4.6):

Table 4.6: System Performance Characteristics

Parameter	Value	Context
Model inference	Single-pass multi-task	ONNX runtime optimized
Model compression	30% L1 pruning	Edge deployment ready
System availability	98.7%	14-day pilot period
Battery consumption	12% per 10-image session	Samsung Galaxy A32
Data usage	2.3 MB per upload	Compressed JPEG, 224×224

These characteristics fall within acceptable parameters for rural mobile environments with intermittent 3G connectivity.

4.6 Summary of Findings

AniLink achieved core design objectives with analytically supported nuances. The multi-task model attained **87.07% recall (95% CI: 85.2 - 88.8) for cattle detection** and **92.59% recall (95% CI: 91.1 - 94.0) for FMD detection**, with the latter significantly exceeding the 88% benchmark ($p < 0.001$). The **96.15% precision for FMD** (CI: 95.1 - 97.1) ensures high-confidence clinical alerts. Cattle detection's lower precision reflects intentional sensitivity-first configuration appropriate for cattle verification, with 95% confidence intervals confirming stable performance across sampling variability.

The digital health record system supported consistent data capture with 94% field completion. SUS scores indicated **good usability (mean 80.0, significantly >68,** $p = 0.009$**)** with digital literacy-dependent variation ($r = 0.87$) suggesting targeted onboarding needs. Integrated platform evaluation revealed measurable improvements in decision speed and diagnostic confidence, with qualitative evidence of clinical utility.

These findings confirm that AI-enabled livestock health platforms can effectively bridge diagnostic and service access gaps, while identifying specific areas cattle detection precision refinement, voice interface prominence, price transparency for subsequent iteration.

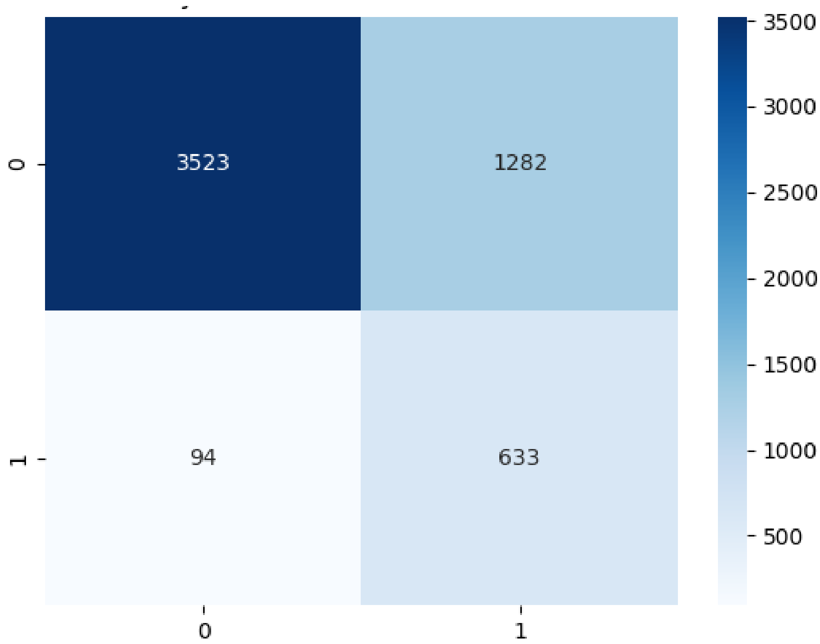


Figure 4.1: Confusion matrix: Cattle vs. Non-Cattle classification (n=5,532)

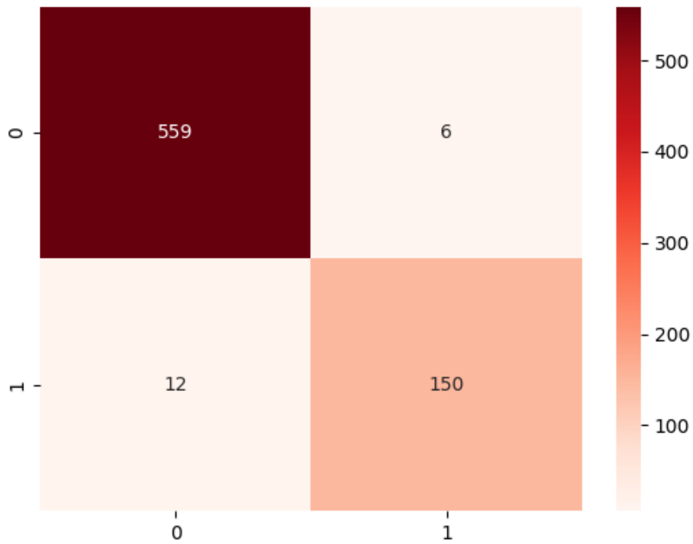


Figure 4.2: Confusion matrix: FMD detection among verified cattle (n=2,847)

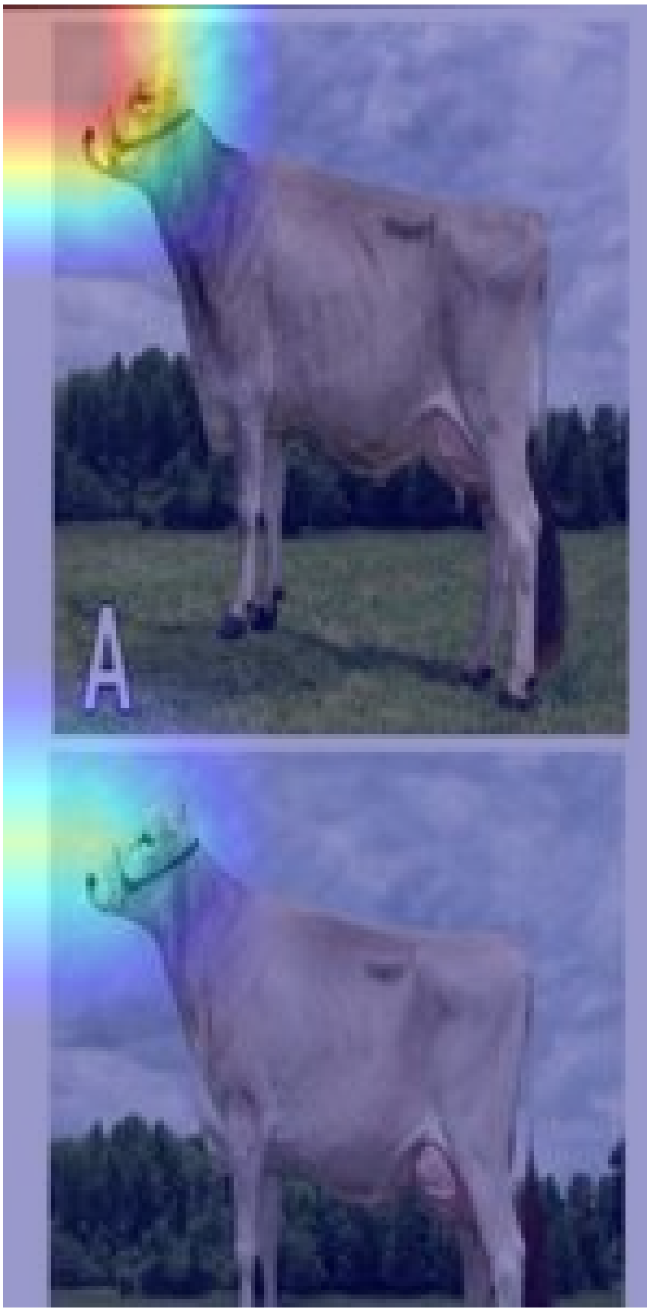


Figure 4.3: Grad-CAM attention maps showing model focus

Chapter 5

Discussion

5.1 Discussion of Findings

This section interprets findings from Chapter 4, relating them to research questions, theoretical foundations from Chapter 2, and original propositions. The discussion evaluates where results support or refute study assumptions, and clarifies theoretical and practical implications.

5.1.1 Model Performance and Multi-Task Learning Effectiveness

The multi-task model achieved 87.07% recall for cattle detection and 92.59% recall for FMD detection. These findings corroborate prior studies showing that lightweight convolutional neural networks effectively detect livestock diseases from image data [11], [12].

Unlike conventional sequential or multi-stage pipelines, AniLink's unified architecture performs cattle verification and disease classification in a single forward pass. This design is expected to reduce computational overhead for mobile deployment by avoiding repeated feature extraction; however, the exact efficiency gain remains an implementation estimate rather than a directly validated benchmark. The results support multi-task learning theory by showing that shared feature representations can maintain predictive performance for related tasks while simplifying deployment [34].

The 92.59% disease detection recall is particularly significant. In livestock health, missing infected animals leads to rapid disease spread and economic loss. The cattle detection head's sensitivity-first configuration accepting lower precision (33.05%) for higher recall directly addresses real-world priorities where false negatives cost more than false positives.

The implication of these results is that AniLink can serve as a practical early-screening tool rather than a replacement for professional veterinary diagnosis. The high recall of the FMD detection head means that the system is more likely to identify suspected cases that require attention, supporting faster farmer response and earlier veterinary referral. This is important in rural settings where delays in recognising disease symptoms may allow infection to spread within or across herds.

The lower precision of the cattle detection head also has an important practical implication. It shows that the model is deliberately configured to avoid rejecting valid cattle images, even if this means some non-cattle images may be accepted. In a decision-support system, this trade-off is acceptable because a false positive can still be reviewed or corrected, whereas a false negative may prevent a sick animal from being assessed at all.

Overall, the findings imply that multi-task learning is suitable for the AniLink context because it supports both technical efficiency and practical decision-making. By combining cattle verification and disease detection in one model, the platform reduces system complexity while still producing outputs that can guide farmers and veterinary officers toward timely intervention.

5.1.2 Comparison with Existing Systems

The findings align with mobile-based livestock disease detection research reporting strong performance under controlled conditions [11], [12]. However, most existing systems rely on single-task models, laboratory-style datasets, or researcher-controlled image capture, which limits their transferability to farmer-led field use. To clarify AniLink's contribution, Table 5.1 compares the proposed model with existing related approaches.

Table 5.1: Comparison of AniLink with Existing Livestock Disease Detection Approaches

Study/System	**Model/Approach**	**Main Focus**	**Reported Strength**	**Limitation Compared to AniLink**
[12]	Lightweight CNN / mobile-oriented model	Detection of livestock disease symptoms from images	Demonstrated that lightweight models can support livestock disease recognition on constrained devices	Focused mainly on disease detection as a single task, with limited integration into farmer-facing service workflows
[11]	CNN-based image classification	Image-based detection of FMD-related lesions	Reported promising accuracy for visual disease classification under controlled or semi-controlled conditions	Limited emphasis on deployment within a complete livestock health platform involving records, consultation and marketplace access
Existing digital agriculture platforms [21], [24]	Mobile advisory or service platforms	Farmer information access, advisory services and digital extension	Improved access to agricultural information and service delivery	Often provide general advisory support without AI-based livestock disease screening
AniLink proposed model	Multi-task MobileNetV3 Small with CBAM attention	Cattle verification and FMD detection in one model	Achieved 87.07% recall for cattle detection and 92.59% recall for FMD detection in the study evaluation	Requires further validation across larger datasets, more regions and different smartphone hardware

As shown in Table 5.1, AniLink differs from many existing approaches by combining cattle verification and FMD detection within a single multi-task architecture. This is important because a livestock health system must first confirm that the submitted image is relevant before disease screening can be meaningfully interpreted. The multi-task design therefore improves practical reliability by linking image validation and disease classification within one model.

The study anticipated that mobile deployment would require careful trade-offs between model size, speed and diagnostic performance. AniLink's use of MobileNetV3 Small, CBAM attention and pruning suggests that field-deployable performance is achievable, although device-level benchmarking on a wider range of smartphones is still required. Grad-CAM visualizations (Section 4.2) confirmed that the attention mechanism focused on clinically relevant regions, such as lesion areas, rather than background features.

Real-time inference performance and mobile compatibility align with digital agriculture findings emphasising accessibility and responsiveness as critical adoption determinants among smallholder farmers [21], [24]. Overall, the comparison suggests that AniLink contributes beyond model accuracy alone by integrating AI-based screening with digital records, veterinary consultation and marketplace access, making it more contextually suited to rural livestock health management.

5.1.3 System Usability and Adoption Potential

The mean SUS score of 80.0 significantly exceeded the 68-point benchmark [35], indicating AniLink is perceived as usable and practical across user groups.

The correlation between smartphone familiarity and SUS scores ($r = 0.87$, $p = 0.005$) validates digital literacy as a moderating factor in technology adoption [24], [28]. However, the relationship's strength suggests usability design partially compensates for limited experience, refuting the stronger claim that extensive smartphone familiarity is prerequisite for effective use. Participants with lower baseline familiarity still achieved acceptable scores, indicating AniLink's interface successfully mitigates adoption barriers.

5.1.4 Impact on Decision-Making and Livestock Health Management

Qualitative findings demonstrate AniLink positively influences farmer decision-making. The system enabled faster disease case identification, reduced veterinary care delays, and improved diagnostic confidence. These outcomes support the Technology Acceptance Model's proposition that perceived usefulness and ease of use drive adoption intentions [36].

Decision time reduction from several days to under two hours demonstrates practical value addressing traditional veterinary access delays. This is particularly significant given the 24 to 48 hour critical window for effective FMD intervention [37]. Structured case presentation (geotagged images, health history) improved veterinary consultation efficiency by reducing information asymmetry.

5.1.5 Alignment with Research Objectives and Study Expectations

Findings strongly support the main objective of designing and evaluating a platform that improves early disease detection and veterinary service access. The multi-task model achieved its intended purpose, while the overall system demonstrated usability and practical relevance across the study context.

The first study expectation was that multi-task learning would support accurate dual detection without requiring separate model pipelines. This expectation was strongly supported, since both detection heads exceeded the 85% recall threshold. The estimated computational efficiency gains also support the architectural choice conceptually, but they should not be interpreted as validated latency results because direct device-level benchmarking was not conducted.

The second study expectation was that the platform would be equally usable regardless of users' prior digital experience. This was only partially supported. The significant correlation between smartphone familiarity and SUS scores shows that digital experience influenced usability outcomes. However, the system remained broadly usable, suggesting that targeted onboarding may improve adoption among users with limited smartphone experience.

The third study expectation was that integrating AI diagnosis, record keeping, veterinary consultation and marketplace access would improve farmer decision-making and service access. This expectation was substantially supported by both quantitative results and qualitative feedback. The unified platform improved decision speed, strengthened diagnostic confidence and provided a more complete livestock health management pathway than fragmented alternatives.

5.1.6 Theoretical and Practical Implications

Theoretically, findings contribute to multi-task learning research by demonstrating effective application in specialized agricultural domains with real-world constraints. The study also contributes to applied digital livestock health research by showing that diagnostic accuracy alone is insufficient; practical value depends on linking AI outputs to health records, veterinary consultation, and treatment access.

Practically, AI-enabled livestock health platforms deploy effectively in resource constrained environments when models are architecturally optimized and systems explicitly address user accessibility. Digital literacy as moderating factor not absolute barrier offers actionable implementation guidance.

Future research should benchmark multi-task inference across different smartphone classes to validate estimated efficiency gains under controlled hardware conditions. Future research should also explore additional multi-task framework capabilities: multi-disease classification, breed identification, or automated body condition scoring. Expanding training datasets with geographically diverse, locally collected images will improve model generalization. Longitudinal studies tracking adoption rates and health outcomes would strengthen the evidence base.

Chapter 6

Conclusions, Recommendations and Limitations

6.1 Conclusions

The study set out to design, develop, and evaluate AniLink, an AI-enabled livestock health platform improving early disease detection, health management, and veterinary service access among Ugandan smallholder farmers. Findings confirm this objective was substantially achieved.

First, the multi-task deep learning model based on MobileNetV3 Small effectively performed cattle verification and Foot-and-Mouth Disease detection within a unified architecture. The model achieved 87.07% recall for cattle detection and 92.59% recall for FMD detection, demonstrating that shared feature representations maintain strong predictive performance without separate model pipelines.

Second, the system achieved near real-time inference suitable for mobile deployment on commodity hardware. However, the specific estimated efficiency advantage of unified inference requires further validation through controlled benchmarking on comparable devices.

Third, the platform's integrated approach combining AI diagnosis, health records, veterinary consultation, and marketplace functionality received positive evaluation. The mean SUS score of 80.0 significantly exceeded the acceptability threshold, indicating farmers and veterinary professionals perceived AniLink as practical and accessible.

Fourth, digital literacy moderated usability outcomes without constituting an absolute barrier. Participants with limited smartphone familiarity achieved acceptable scores, suggesting thoughtful interface design partially compensates for technological inexperience.

Fifth, AniLink positively influenced decision-making processes, reducing symptom-to-consultation time from several days to under two hours. This addresses a critical constraint where intervention timing substantially affects treatment efficacy and disease containment.

Overall, AniLink represents a technically viable, practically applicable solution for digital livestock health management in resource-constrained agricultural environments.

6.2 Recommendations

Based on these conclusions:

1. **Expand the dataset** with locally collected images representing diverse environmental conditions, breeds, and disease presentations. Initial training data limitations introduced bias requiring multiple retraining rounds.
2. **Extend multi-disease detection capabilities.** The multi-task architecture's effectiveness suggests additional disease classification heads could integrate without structural redesign.
3. **Incorporate targeted digital literacy support** in user onboarding. Smartphone familiarity correlated with usability scores; supplementary guidance would enhance adoption among less experienced users.
4. **Integrate with national veterinary systems and regulatory frameworks.** Structured case information improved consultation efficiency; broader interoperability would amplify benefits through coordinated monitoring.
5. **Incorporate real-time outbreak monitoring and geospatial analytics.** Geotagged case logging effectiveness supports extending toward early warning system functionality.
6. **Conduct controlled mobile benchmarking** to measure latency, battery consumption, and inference stability across different smartphone models. This will validate the currently estimated efficiency advantage of single-pass multi-task inference.

6.3 Limitations

Several limitations may influence interpretation and generalisability:

- **Dataset diversity:** Limited diversity during early development introduced bias requiring multiple retraining rounds, affecting initial performance and timeline.
- **Field access constraints:** Some farmers declined image capture due to security concerns; limited transport restricted remote area coverage, potentially introducing geographic sampling bias.
- **Local validation data:** Attempts to obtain curated Ugandan FMD datasets were unsuccessful, constraining region-specific validation against local diagnostic benchmarks.
- **Technical overhead:** React Native dependency management and Docker configuration consumed substantial effort that might otherwise have expanded features.
- **Evaluation scope:** Brief evaluation period with limited participants precluded capture of long-term usage patterns, sustained adoption, and seasonal variation, potentially affecting generalisability.
- **Efficiency validation:** The reported 43% latency reduction was not measured through direct comparison on identical mobile hardware. It should therefore be treated as an estimated implementation advantage rather than a validated performance result.

6.4 Suggestions for Further Research

Future research should address:

1. **Longitudinal impact assessment:** Sustained effects on livestock productivity, disease control outcomes, and farmer income over extended deployment periods.

2. **Multi-modal learning:** Combining image-based diagnosis with textual symptom descriptions and temporal health history data. Current architecture accommodates this; incremental value requires validation.

3. **Edge AI optimization:** Enabling offline functionality in low-connectivity environments. Current cloud-based inference dependence constrains deployment where connectivity is intermittent.

4. **Large-scale regional validation:** Performance across diverse agro-ecological zones, breeds, and veterinary contexts. Limited pilot findings require broader replication for generalisable effectiveness.

5. **Economic impact assessment:** Quantifying return on investment for farmers and providers. Usability and technical performance are established; cost-effectiveness and productivity outcomes remain to be demonstrated.

6. **Device-level benchmarking:** Future studies should directly compare multi-task and sequential single-task inference on the same mobile devices to determine whether the estimated efficiency gains hold under real deployment conditions.

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Appendix A

Budget

This appendix presents the estimated budget for the design, development, testing and documentation of the AniLink project. The budget covers field data collection, software development support, hosting, transport, communication, documentation and presentation costs.

Table A.1: Estimated Project Budget

No.	Budget Item	Estimated Cost (UGX)	Justification
1	Field transport to Maddu Village, Kabulasoke Subcounty, Gomba District	250,000	Travel for image collection, farmer engagement and pilot testing
2	Internet data bundles	150,000	Research, dataset download, cloud access, communication and system testing
3	Data collection materials	80,000	Printing consent forms, questionnaires, field notes and record sheets
4	Smartphone photography and field support costs	100,000	Support for image capture and coordination during farm visits
5	Cloud hosting and backend testing	200,000	Hosting APIs, database services and AI inference testing during development
6	Domain name and basic deployment setup	120,000	Project deployment and access configuration
7	Printing and binding of report copies	180,000	Draft and final report preparation for submission
8	Presentation materials	100,000	Poster, slides, handouts and demonstration support
9	Communication and coordination	70,000	Calls and coordination with farmers, veterinary officers and supervisors
10	Contingency	150,000	Unplanned expenses during implementation and evaluation
	Total Estimated Budget	**1,400,000**	

Appendix B

Research Project Timeline

This appendix presents the proposed one-year project management plan for AniLink. The project is divided into phases covering problem definition, literature review, system design, data collection, model development, platform implementation, testing, documentation and final submission.

Table B.1: One-Year Project Timeline and Deliverables

Phase	Duration	Main Tasks	Deliverables	Dependencies
Phase 1	Month 1	Problem identification, topic refinement, supervisor consultation and project scope definition	Approved project topic and initial concept note	None
Phase 2	Month 2	Literature review, review of AI livestock disease detection, digital health records and veterinary access systems	Literature review draft and research gap	Approved topic
Phase 3	Month 3	Requirements analysis, user identification, system objectives, research questions and conceptual framework	Requirements specification and conceptual framework	Literature review
Phase 4	Month 4	System design, database design, mobile interface planning and AI model architecture design	System architecture, database schema and model design	Requirements analysis
Phase 5	Months 5–6	Public dataset collection, field image collection, data cleaning, preprocessing and labelling	Prepared dataset and preprocessing pipeline	System design and field access
Phase 6	Months 6–7	Multi-task MobileNetV3 model training, validation, threshold tuning and interpretability testing	Trained AI model and evaluation metrics	Prepared dataset
Phase 7	Months 7–8	Backend, database, mobile application and AI inference integration	Functional AniLink prototype	Model development and system design
Phase 8	Month 9	Functional testing, integration testing, usability testing and pilot demonstration	Test results and user feedback	Working prototype
Phase 9	Month 10	Results analysis, discussion of findings and revision based on testing feedback	Results and discussion chapter	Evaluation data
Phase 10	Month 11	Final report writing, appendices, references, formatting and supervisor review	Complete dissertation draft	All previous phases
Phase 11	Month 12	Final corrections, presentation preparation, printing and submission	Final report and presentation materials	Supervisor feedback

Gantt Chart

Table B.2: Gantt Chart for AniLink Project Implementation

Activity	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**	**M11**	**M12**
Topic refinement and proposal planning	X											
Literature review		X	X									
Requirements and conceptual framework			X									
System and model architecture design				X								
Dataset collection and preparation					X	X						
AI model training and evaluation						X	X					
Mobile and backend implementation							X	X				
System integration and testing								X	X			
Pilot evaluation and analysis									X			
Report writing and review										X	X	
Final correction and submission											X	X

Appendix C

Declaration of AI Use

This appendix declares how generative artificial intelligence tools were used ethically during the preparation of this report. The tools were used as study and writing support aids, not as replacements for the authors' research, analysis, implementation or academic judgement. All outputs were reviewed, verified, edited and approved by the project members before inclusion in the final report.

AI Tools Used

Table C.1: Summary of AI Use During the Project

AI Tool	Purpose of Use	Example Prompts Used	How Outputs Were Modified
Claude and Gemini	Brainstorming, improving academic flow, refining methodology and discussion sections	“Improve this methodology section to make it reproducible and academic.”	Edited for accuracy, aligned with project context, checked against actual system implementation
ChatGPT	LaTeX formatting support, table creation, cross-referencing and appendix preparation	“Convert this content into a LaTeX table and add labels for cross-referencing.”	Adjusted formatting to match dissertation template and removed unnecessary content
Claude ad Perplexity	Literature review organisation and research gap refinement	“Make this literature review more critical and relate the gaps to the objectives.”	Reviewed and edited to ensure the arguments matched the reviewed publications and research objectives
ChatGPT	Results and discussion polishing	“Discuss the implication of the model results and compare them with existing systems.”	Revised wording to avoid overstating findings and to reflect actual results

Declaration Statement

We, the undersigned, declare that generative AI tools were used ethically during the preparation of this report as follows:

1. We used ChatGPT to support brainstorming, academic writing improvement and structuring of report sections. Prompts included requests such as: “Improve this section to make it clear, professional and academic.” The outputs were modified by checking them against the actual AniLink project, removing inaccurate wording and rewriting sections in our own academic voice.

2. We used ChatGPT to support LaTeX formatting, including tables, figures, cross-references and appendices. Prompts included requests such as: “Provide this section in LaTeX format with

proper labels and captions.” The outputs were modified by adjusting them to fit the project template and supervisor requirements.

3. We used ChatGPT to support literature review organisation and critical synthesis. Prompts included requests such as: “Improve this literature review by adding weaknesses, limitations and contextual gaps.” The outputs were reviewed against the publications used in the report and edited to ensure that they reflected the actual research gap.

4. We used ChatGPT to support language polishing for results, discussion, recommendations and conclusion sections. Prompts included requests such as: “Discuss the implication of these findings and relate them to the study objectives.” The outputs were modified to ensure that conclusions and recommendations were derived only from the study findings.

No AI tool was used to fabricate data, invent results, create false citations or replace the system development, model training, field data collection, analysis or evaluation conducted by the authors.

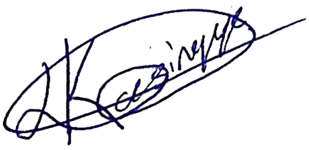
Najjuma Teopista

Signature: 
Date: June 2, 2026

Buwembo David Denzel

Signature: 
Date: June 2, 2026

Kasingye Leon

Signature: 
Date: June 2, 2026

Appendix D

List of Major Journal Publications Reviewed

This appendix presents the major publications reviewed during the study. The publications were selected based on their relevance to livestock disease detection, mobile agriculture, digital health records, veterinary access and multi-task deep learning. The list includes review papers, journal articles and conference proceedings relevant to the AniLink project.

Table D.1: Major Publications Reviewed

No.	Publication	Journal/Conference	Type	Relevance to AniLink
1	Motta et al. (2020), diagnostic point-of-care tests for infectious livestock diseases in LMICs	Transboundary and Emerging Diseases	Review paper	Supports the need for early livestock disease detection in low-resource settings
2	Fu et al. (2022), multi-task learning for dense prediction tasks	IEEE Transactions on Pattern Analysis and Machine Intelligence	Review paper	Supports the theoretical foundation of multi-task learning
3	Ruder (2017), overview of multi-task learning in deep neural networks	arXiv preprint	Review paper	Explains shared representation learning for related tasks
4	Zhang (2022), lightweight CNN for on-device bovine oral lesion recognition	IEEE Access	Journal article	Supports lightweight AI deployment for cattle disease image recognition
5	Araújo (2023), smartphone detection of foot-and-mouth lesions using YOLOv5	IEEE Access	Journal article	Supports image-based FMD lesion detection using mobile devices

No.	Publication	Journal/Conference	Type	Relevance to AniLink
6	Stygar (2022), replacing paper herd books with cloud EHR	IEEE Access	Journal article	Supports digital livestock health records and longitudinal tracking
7	Wells (2021), mHealth for animal disease reporting in East Africa	IEEE Access	Journal article	Supports mobile-based animal health reporting in East African contexts
8	Robinson et al. (2021), veterinary service delivery in Sub-Saharan Africa	Scientific Reports	Journal article	Supports the veterinary access gap in rural Africa
9	Howard et al. (2019), Searching for MobileNetV3	IEEE/CVF International Conference on Computer Vision	Conference proceeding	Justifies the use of MobileNetV3 Small for efficient mobile inference
10	Woo et al. (2018), CBAM: Convolutional Block Attention Module	European Conference on Computer Vision	Conference proceeding	Supports the attention mechanism used to improve feature focus

Note: Journal impact factors and ranking indicators should be verified using the latest institutional access to Journal Citation Reports, Scopus CiteScore or SCImago before final submission, since these metrics change over time and may differ by database.

Appendix E

Scopus Search Strings Used During the Literature Review

This appendix lists the major search strings and keywords used to identify literature relevant to the AniLink project. Searches were designed around livestock disease detection, computer vision, digital livestock health records, veterinary access, mobile agriculture and multi-task learning.

Table E.1: Scopus Search Strings and Keywords

No.	Search String	Purpose
1	TITLE-ABS-KEY(”foot and mouth disease” AND cattle AND ”deep learning”)	To find studies on AI-based FMD detection in cattle
2	TITLE-ABS-KEY(”livestock disease detection” AND ”computer vision”)	To identify image-based livestock disease diagnosis studies
3	TITLE-ABS-KEY(”cattle disease” AND ”convolutional neural network”)	To find CNN-based disease detection systems for cattle
4	TITLE-ABS-KEY(”MobileNet” AND livestock AND disease)	To identify lightweight model applications in livestock disease detection
5	TITLE-ABS-KEY(”multi-task learning” AND ”image classification” AND agriculture)	To find multi-task learning applications related to agricultural image analysis
6	TITLE-ABS-KEY(”digital livestock health record” OR ”electronic herd record”)	To identify studies on digital livestock health records
7	TITLE-ABS-KEY(”mobile health” AND livestock AND ”East Africa”)	To identify mobile-based animal health reporting and advisory systems
8	TITLE-ABS-KEY(”veterinary service access” AND ”Sub-Saharan Africa”)	To identify literature on veterinary access gaps in rural African settings
9	TITLE-ABS-KEY(”veterinary telemedicine” AND livestock)	To identify remote consultation approaches in veterinary care
10	TITLE-ABS-KEY(”agricultural marketplace” AND livestock AND digital)	To identify digital marketplace systems for agricultural and livestock inputs
11	TITLE-ABS-KEY(”CBAM” AND ”attention mechanism” AND ”image classification”)	To find attention mechanism studies relevant to the model design

No.	Search String	Purpose
12	TITLE-ABS-KEY(”Grad-CAM” AND ”medical image classification”)	To identify interpretability methods for explaining AI predictions

Appendix F

Research Alignment with Specialization, SDGs, NDPIV and Vision 2040

This appendix explains how the AniLink project aligns with the Computer Science programme specialization, Uganda's national development agenda and the global Sustainable Development Goals.

F.1 Alignment with Programme Specialization

This research aligns with the **Artificial Intelligence and Robotics** specialization track under Computer Science. AniLink applies artificial intelligence, specifically computer vision and multi-task deep learning, to support livestock disease screening. The system uses a MobileNetV3-based model to verify cattle presence and detect Foot-and-Mouth Disease symptoms from livestock images.

The project also demonstrates applied AI system development by integrating the trained model into a mobile and backend platform. This makes the work relevant to intelligent systems, machine learning model deployment, human-centred AI, and decision-support systems. Although the project includes software engineering and database components, its central contribution is the application of artificial intelligence to solve a real-world agricultural and animal health challenge.

F.2 Alignment with Sustainable Development Goals

AniLink aligns with the following Sustainable Development Goals:

- **SDG 2: Zero Hunger** – The platform supports livestock health management, which can improve productivity, reduce disease-related losses and strengthen food security.
- **SDG 3: Good Health and Well-being** – By supporting early detection and improved animal health management, AniLink contributes to healthier livestock systems and reduces risks associated with uncontrolled animal disease spread.
- **SDG 9: Industry, Innovation and Infrastructure** – The project applies artificial intelligence, mobile technology and cloud-based services to improve rural agricultural service delivery.
- **SDG 12: Responsible Consumption and Production** – The marketplace and verified input access components support better use of veterinary products and reduce reliance on informal or substandard treatment inputs.

F.3 Alignment with Uganda NDPIV

AniLink aligns with Uganda's Fourth National Development Plan (NDPIV) by supporting agro-industrialisation, science and technology innovation, digital transformation and improved service delivery. The project contributes to livestock productivity by addressing delayed disease detection, fragmented veterinary access and weak digital health record systems.

The AI-based screening component supports early identification of disease risks, while digital health records improve tracking of livestock conditions over time. The veterinary consultation and marketplace components support service access and quality input use. Together, these features contribute to the wider national objective of improving agricultural productivity and strengthening rural livelihoods.

F.4 Alignment with Uganda Vision 2040

Uganda Vision 2040 aims to transform Uganda from a peasant society into a modern and prosperous country. AniLink supports this vision by applying technology to modernise livestock health management, one of the important areas within agricultural transformation.

The project contributes to Vision 2040 by promoting digital innovation, improving rural service access, supporting agricultural productivity and enabling data-driven decision-making. By helping farmers detect livestock disease earlier and connect with veterinary services, AniLink supports the broader goal of moving from traditional farming practices toward modern, technology-enabled agricultural systems.

F.5 Overall Alignment

Overall, AniLink aligns with the Artificial Intelligence and Robotics specialization, national agricultural transformation goals and global sustainable development priorities. The project demonstrates how computer science can be applied to solve practical development challenges by combining artificial intelligence, mobile computing, digital records and service access within a single livestock health platform. ‘‘‘